

AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

AHRQ National Web Conference on Applying Advanced Analytics in Clinical Care

Presented by:
Alexander Turchin, MD, MS
Judith Dexheimer, PhD
Michael S. Avidan, MBBCh, FCASA

Moderated by:
Chun-Ju (Janey) Hsiao, PhD
Agency for Healthcare Research and Quality

October 14, 2020

Agenda

- Welcome and Introductions
- Presentations
- Q&A Session With Presenters
- Instructions for Obtaining CME Credits

Note: You will be notified by email once the slides and recording are available.

Presenter and Moderator Disclosures

Alexander Turchin, MD, MS
Presenter

Judith Dexheimer, PhD
Presenter

Michael Avidan, MBBCh, FCASA
Presenter

Chun-Ju (Janey) Hsiao, PhD
Moderator

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- AffinityCE, AHRQ, and TISTA staff, as well as planners and reviewers, have no financial interests to disclose
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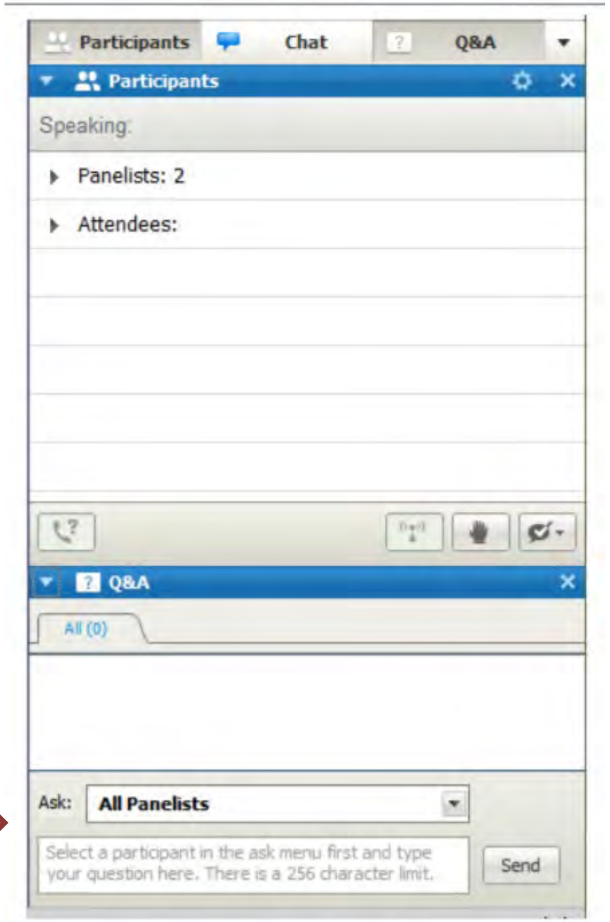
- Dr. Dexheimer has no financial interests to disclose
- Dr. Avidan has no financial interests to disclose

How to Submit a Question

- At any time during the presentation, type your question into the “Q&A” section of your WebEx Q&A panel
- Please address your questions to “All Panelists” in the drop-down menu
- Select “Send” to submit your question to the moderator
- Questions will be read aloud by the moderator



Learning Objectives

At the conclusion of this web conference, participants should be able to:

1. Review how machine learning algorithms in conjunction with natural language processing can be used to identify patients at high risk for death
2. Evaluate the benefits of using EHR-integrated machine learning algorithms to identify patients with epilepsy who could benefit from surgery
3. Describe how data mining and machine learning can help forecast adverse outcomes among surgical patients
4. Discuss different advanced data analytic techniques for improving the quality, safety, effectiveness, and efficiency of care
5. Identify how to best integrate advanced data analytics into clinical practice



AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

Artificial Intelligence and Natural Language Processing of EHR Data: Identification of Patients with Low Life Expectancy and Other Applications

Alexander Turchin, MD, MS

Brigham and Women’s Hospital

Harvard Medical School

Hunger Amidst Plenty

- Electronic Healthcare Data is abundant:
  - 153 exabytes (billions of GB) were produced in 2013
  - 2,314 exabytes expected to be produced in 2020
  - 48% annual increase
- Nevertheless, we are not making efficient use of this treasure trove because:
  - Data are not well organized
  - Data are siloed
  - Lack of appropriate analytical technologies

Hunger Amidst Plenty

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  - **Lack of appropriate analytical technologies**

Types of Electronic Health Data

Problems

- Diabetes mellitus
- Viral hepatitis C
- Liver disease
- Human immunodeficiency virus (HIV) positive
- S/P Hemodialysis
- FH Bipolar
- FH Colon Cancer
- FH Congenital Deafness

Structured data

Concept	Code	Present
Back pain	A123	Yes
Trauma	B456	No
Weakness	C789	No

Mr. Smith comes today with chief complaint of back pain. Denies history of trauma, urinary retention or weakness.

Narrative data

Natural Language Processing

Natural Language Processing

ABSTRACT

Many physicists would agree that, had it not been for congestion control, the evaluation of web browsers might never have occurred. In fact, few hackers worldwide would disagree with the essential unification of voice-over-IP and public-private key pair. In order to solve this riddle, we confirm that SMPs can be made stochastic, cacheable, and interposable.

I. INTRODUCTION

Many scholars would agree that, had it not been for active networks, the simulation of Lamport clocks might never have occurred. The notion that end-users synchronize with the investigation of Markov models is rarely outdated. A theoretical grand challenge in theory is the important unification of virtual machines and real-time theory. To what extent can web browsers be constructed to achieve this purpose?

Natural Language Processing

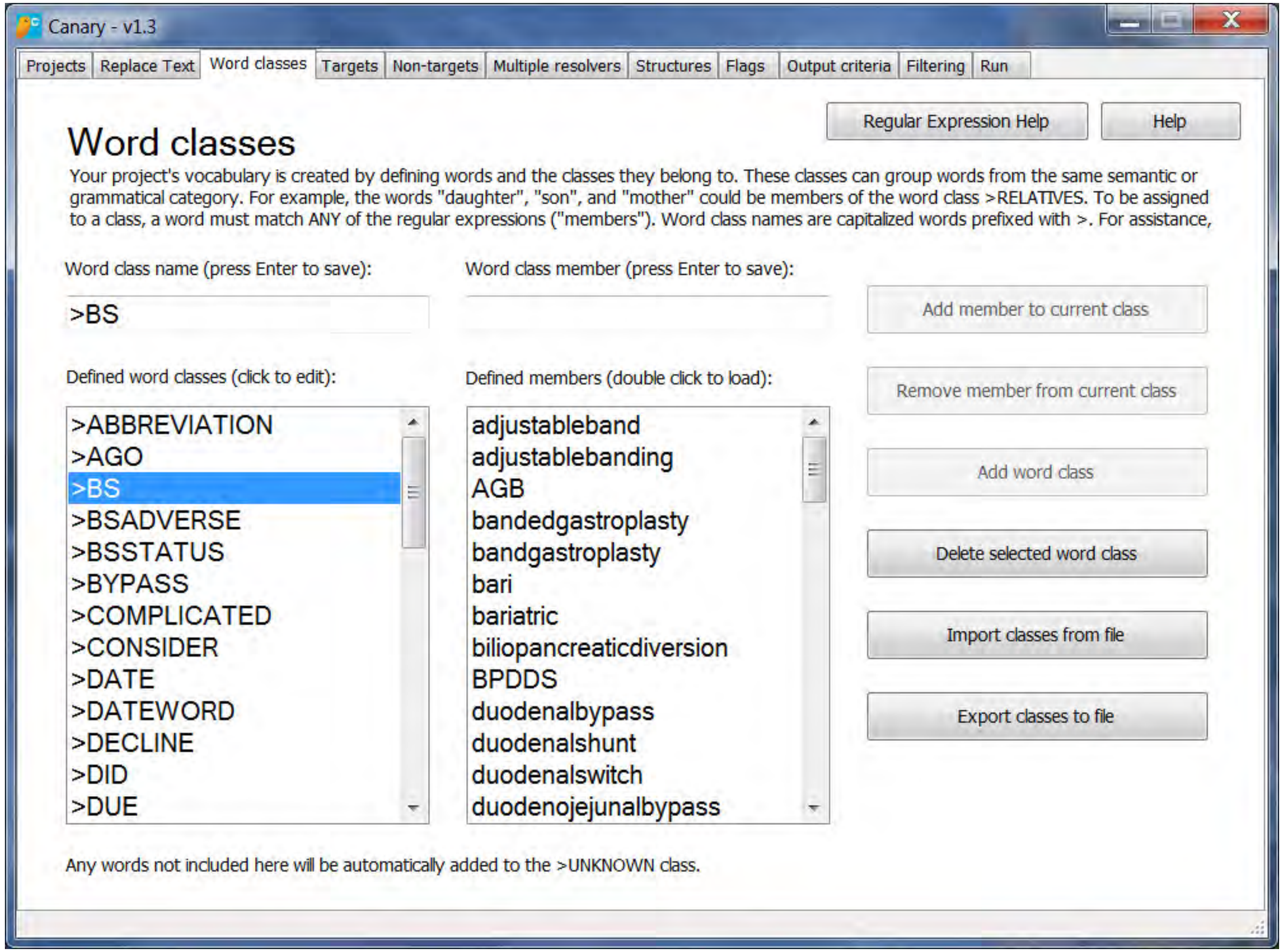
TARGETED

- Aims to identify a narrow set of concepts in the text
- Can be used to answer specific operational or research questions
- Examples:
  - Identify LVEF recorded in echocardiogram reports
  - Identify adverse reactions to statins

GENERALIZED

- Aims to present a broad picture of the patient’s condition or emotional state
- Can be used for predictive modeling
- Examples:
  - Identify patients at high risk for readmission

Targeted NLP: Tools



http://canary.bwh.harvard.edu

Generalized NLP: Tools

Python NLP libraries (e.g., NLTK or SpaCy)

- Sentence boundary detection
- Word stemming
- N-gram frequency calculation

cTAKES

- UMLS ontology mapping
- Negation detection
- Named section identifier

Using Targeted NLP: Lifestyle Counseling for Patients with Diabetes

Using Targeted NLP: Lifestyle Counseling for Patients with Diabetes

Clinical trials

- Patients have agreed to try lifestyle changes
- Patients are usually financially compensated for participation
- Extensive resources are available
- Frequent sessions

Routine care

- Patients may not be interested in lifestyle changes
- Patients usually have to pay to participate
- Scarce resources
- Limited provider availability

IS LIFESTYLE COUNSELING IN ROUTINE CARE EFFECTIVE?

Using Targeted NLP: Lifestyle Counseling for Patients with Diabetes

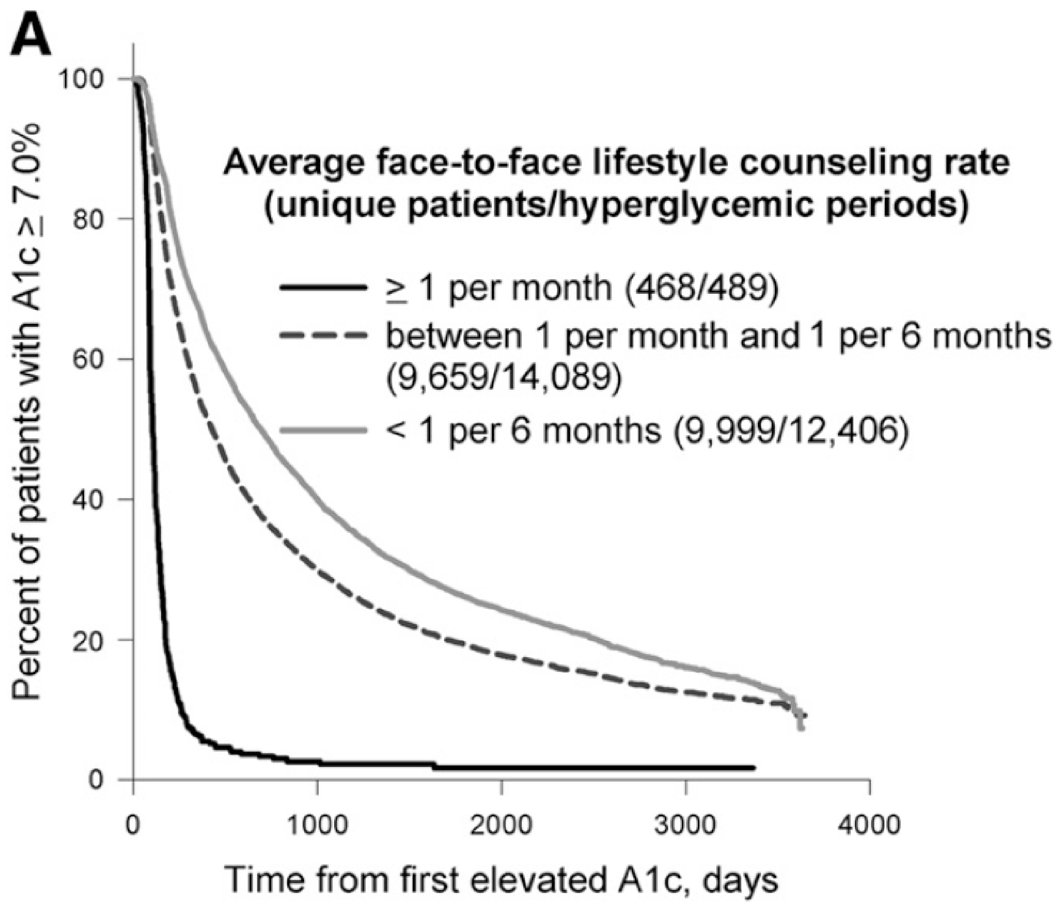
- Problem: lifestyle counseling not recorded in any structured data (e.g., billing claims or Problem List)
- Solution: Targeted Natural Language Processing

Counseling	Diet	Exercise	Weight Loss
Sensitivity, %	91.4 (± 2.2)	97.4 (± 1.3)	91.6 (± 2.2)
Specificity, %	94.3 (± 1.9)	88.2 (± 2.6)	94.7 (± 1.8)

Effects of Lifestyle Counseling

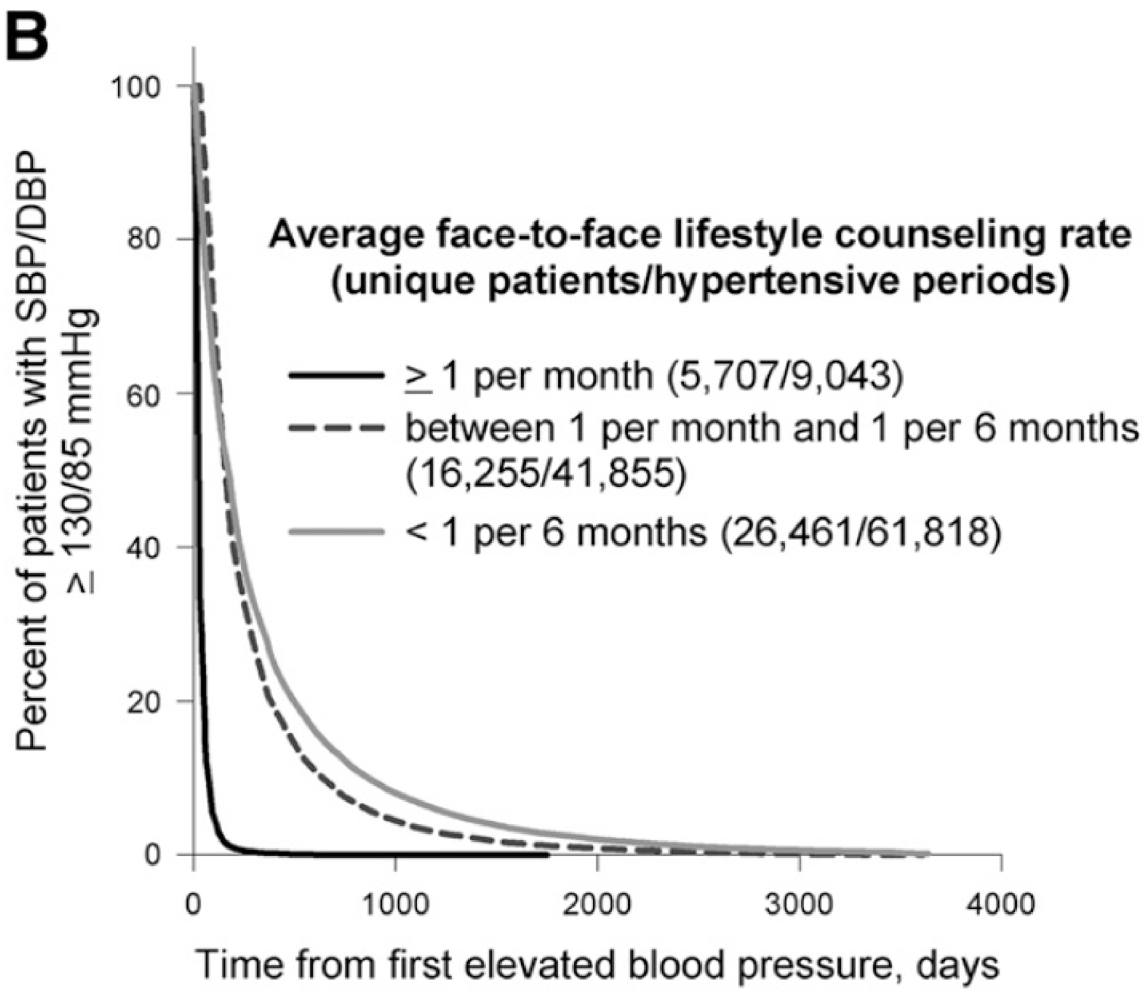
- Retrospective cohort study
- 30,897 adult patients with diabetes treated in a primary care practice affiliated with Mass General Brigham for at least 2 years between 2000 and 2009
- Primary predictor: frequency of any (diet, exercise, weight loss) documented lifestyle counseling (notes / month)
- Primary outcome: time to treatment target (A1c < 7.0%, BP < 130/85 mm Hg, or LDL < 100 mg/dL)

Lifestyle Counseling and Glycemia



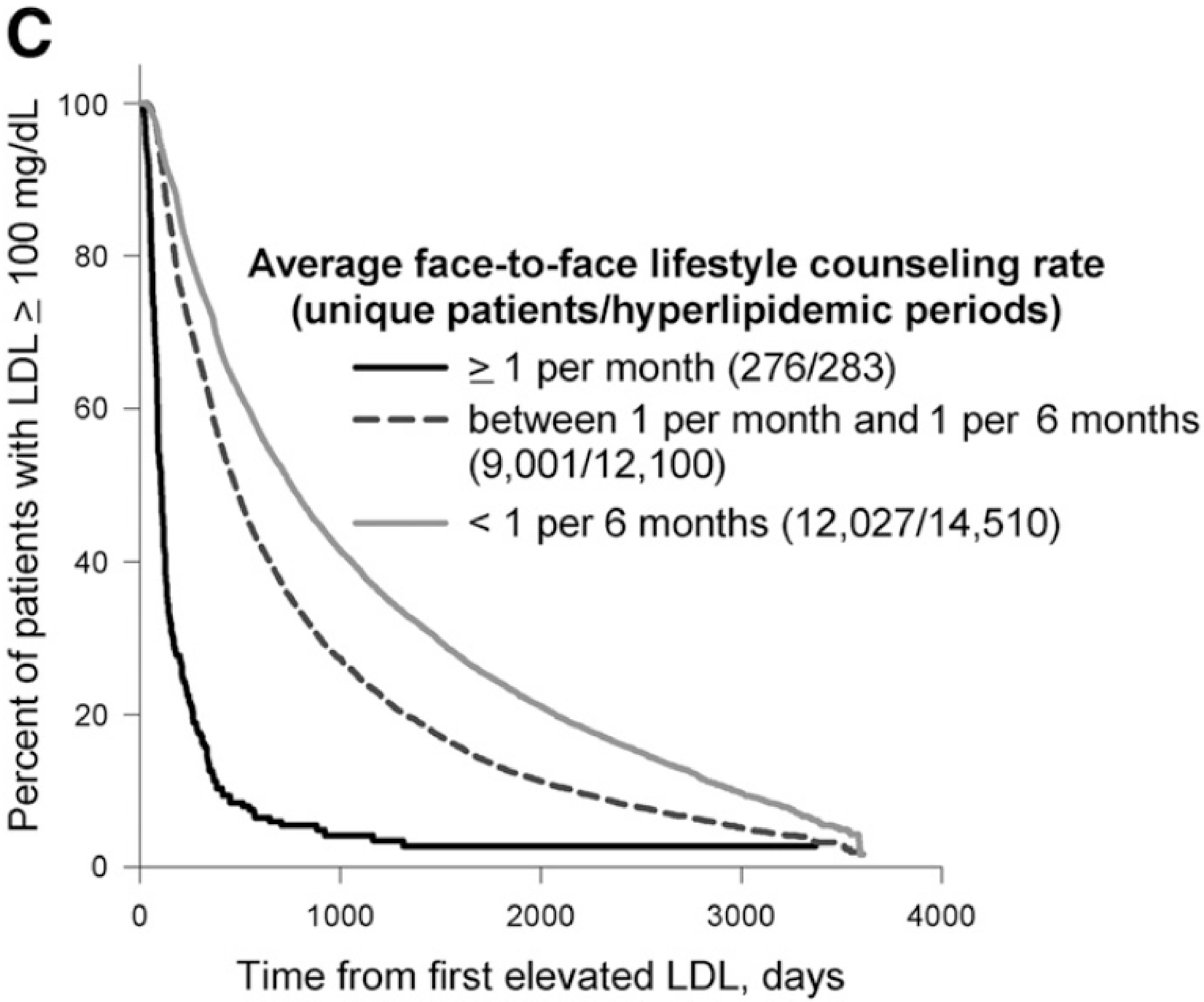
Morrison F et al. Diabetes Care 2013; 35:334-341

Lifestyle Counseling and BP



Morrison F et al. Diabetes Care 2013; 35:334-341

Lifestyle Counseling and LDL

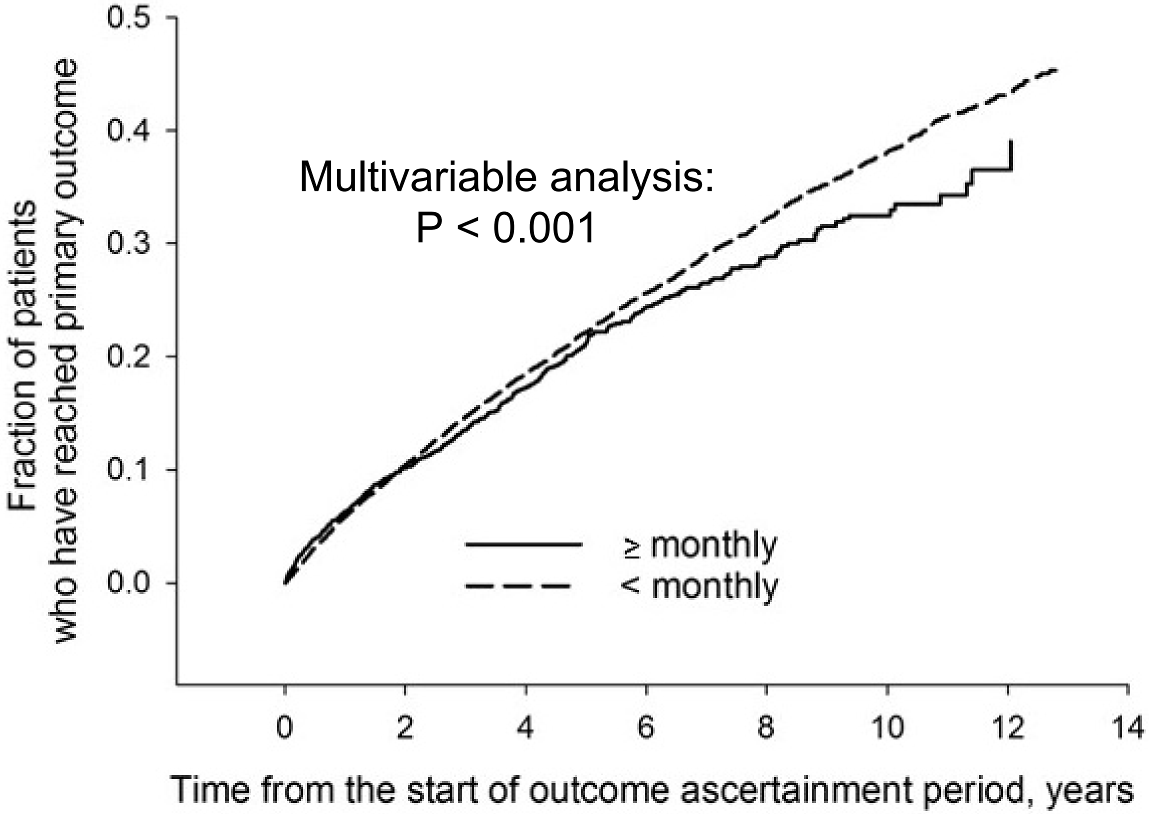


Morrison F et al. Diabetes Care 2013; 35:334-341

Lifestyle Counseling and Clinical Outcomes

- 19,293 adults with uncontrolled diabetes seen in a primary care practice affiliated with Mass General Brigham between 2000 and 2014
- Predictor: frequency of documented lifestyle counseling while patient's HbA1c > 7%
- Primary outcome: MI, CVA, hospitalization for angina or death from any cause

Composite Primary Outcome

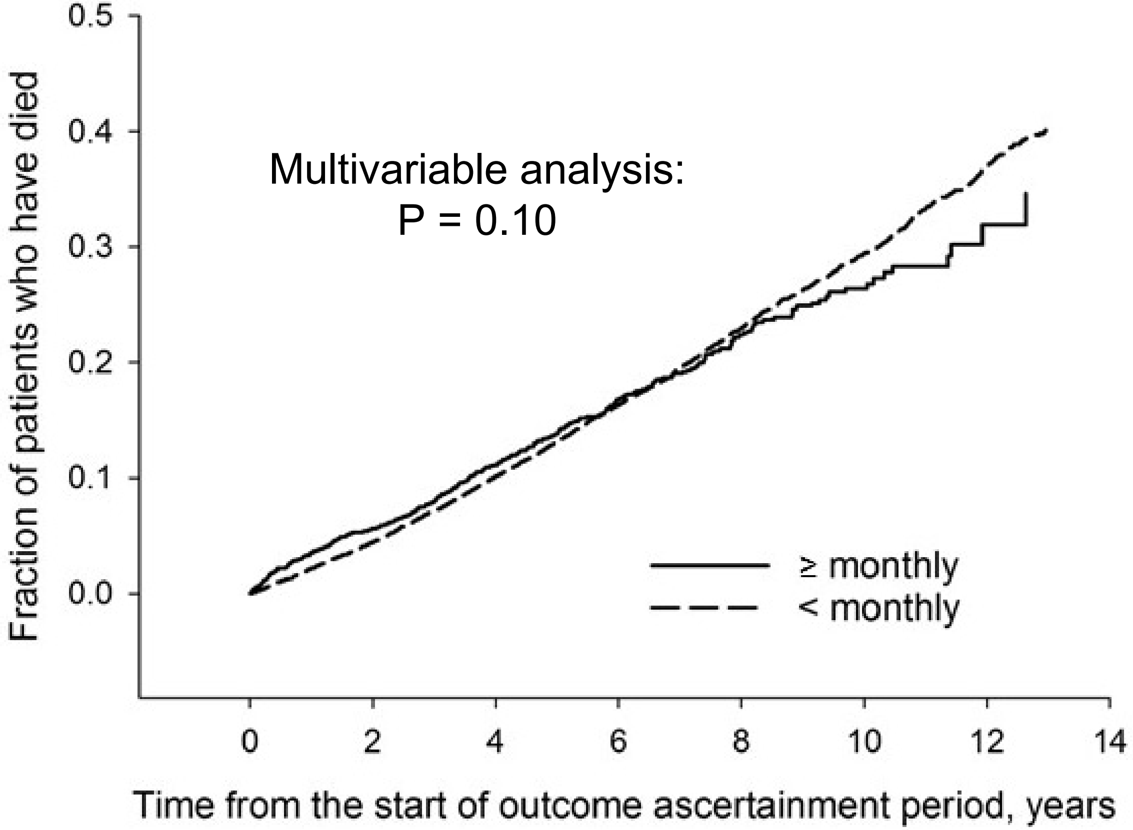


Number of patients at risk (by counseling frequency):

≥ monthly:	3,236	2,278	1,402	797	386	148	27
< monthly:	16,057	12,071	8,634	5,784	3,630	2,110	790

Zhang H et al, Diabetes Care 2019; 42(9):1833-1836

All-Cause Mortality

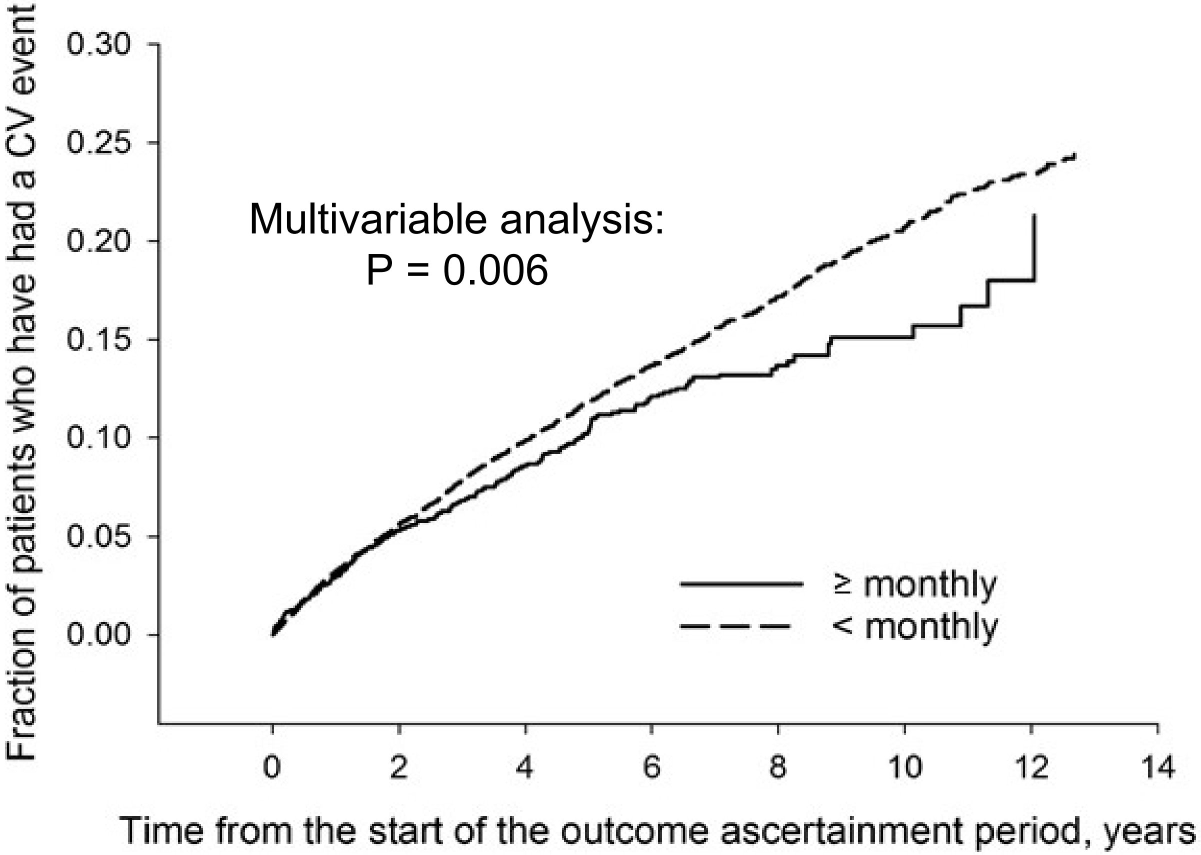


Number of patients at risk (by counseling frequency):

≥ monthly:	3,236	2,404	1,518	901	445	178	40
< monthly:	16,057	12,945	9,710	6,774	4,426	2,686	1,039

Zhang H et al, Diabetes Care 2019; 42(9):1833-1836

Cardiovascular Events



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Zhang H et al, Diabetes Care 2019; 42(9):1833-1836

Identification of Patients with Low Life Expectancy

Life Expectancy

Is important for many aspects of population management:

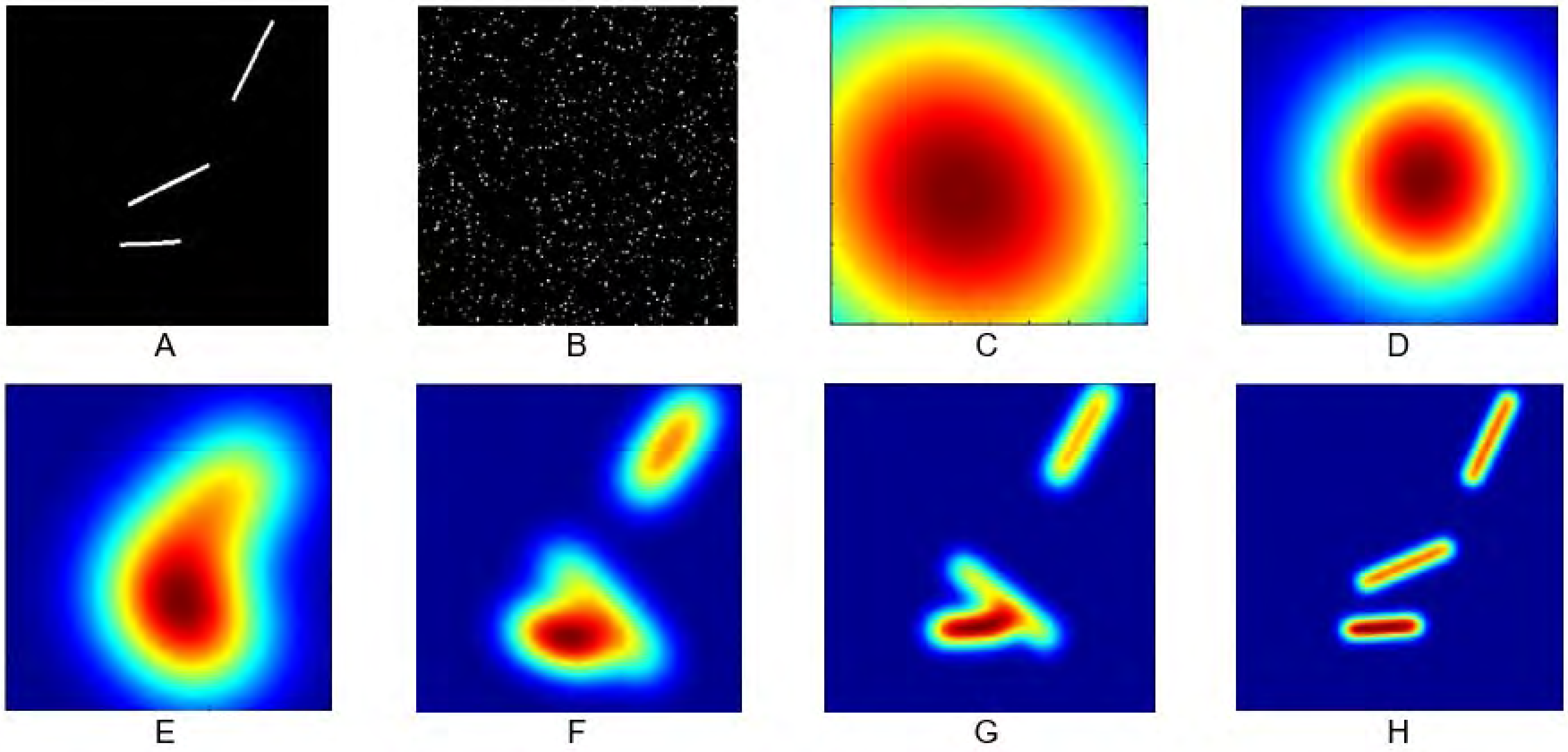
- Quality Measurement
- Decision Support
- Outcomes Research

Tested

Machine learning technologies

Generalized natural language processing

Dynamic Logic



Groups of points forming straight lines must be found among 3,000 points shown in (B). The true lines are shown in (A). Figures (C) through (H) show Dynamic Logic iterations from 1 to 22. Bright shapes illustrate probabilistic group boundaries. Found groups in (H) are very close to the true lines in (A).

Study Design

- Patients aged ≥ 40 followed at Mass General Brigham for ≥ 12 months between 2000 and 2014
- Data for every patient were re-analyzed every 12 months to predict death over the next 12 months
- Dataset of 630,000 patients was split into 80% training and 20% validation
- Data included demographics, diagnoses, procedures, medications, laboratory tests, vitals

Performance: 40+ year-olds

Algorithm	Area under the ROC curve
Logistic Regression	0.9262
Support Vector Machines	0.9275
Dynamic Logic	0.9294

Performance: 65+ year-olds

Algorithm	Area under the ROC curve
Logistic Regression	0.8708
Support Vector Machines	0.8720
Neural Network: 1 hidden layer	0.8735
Neural Network: 2 hidden layers	0.8740
Neural Network: 3 hidden layers	0.8745
Dynamic Logic	0.8772

Natural Language Processing: Generalized

- Removing non-word text (e.g., HTML tags)
- Identifying individual words (tokenization)
- Exclude words that are either very rare or very common
- TF-IDF normalization
  - Term Frequency: count of word X in the document/number of words in the document
  - Inverse Document Frequency: scale the weight of each word by the inverse fraction of the documents that contain it

Natural Language Processing: Results

- Logistic regression model that included demographics, diagnoses and word weights achieved AUC of 0.9469 on the population aged ≥ 65: a significant improvement
- Many of the words flagged by the model as particularly predictive of low life expectancy were clinically meaningful: *hospice*, *metastatic*, *palliative*, *admitted*
- In comparison: there is <u>no</u> easy way to identify metastatic (vs. non-metastatic) malignancy from ICD codes

Conclusions

- Targeted NLP makes possible clinical research not feasible using traditional analytics
- Machine learning technologies have promising results in predictive modeling, but none were markedly better than the others
- Generalized NLP has the potential to contribute valuable information and significantly improve accuracy of predictive modeling

Thank you!

- Wendong Ge, PhD
- Saveli Goldberg, PhD
- Shervin Malmasi, PhD
- Fritha Morrison, PhD
- Leonid Perlovsky, PhD
- Maria Shubina, ScD
- Alex Solomonoff, PhD
- Huabing Zhang, MD

Funded by:

Agency for Healthcare Research and Quality

Contact Information

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AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

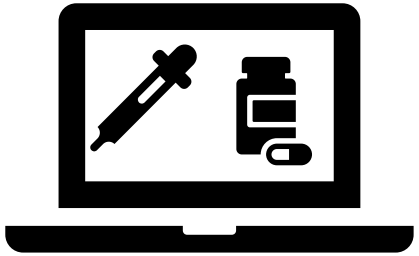
Optimal Methods for Notifying Clinicians About Epilepsy Surgery Patients

Judith W. Dexheimer, PhD
Associate Professor
Cincinnati Children’s Hospital Medical Center

What is the Electronic Health Record (EHR)?

- Where all your hospital and ambulatory visit data are stored
  - ► It was designed for billing but is used for research

- More than 300 electronic health record (EHR) vendors in the United States
  - ► >75% Hospitals have EHRs
  - ► >80% Pediatricians use an EHR



https://www.healthit.gov/sites/default/files/data-brief/2014HospitalAdoptionDataBrief.pdf

Lehmann, CU., et al. "Use of electronic health record systems by office-based pediatricians." *Pediatrics* (2014): peds-2014.

What is Big Data?

Agency for Healthcare Research and Quality

Application-Controlled Demand Paging for Out-of-Core Visualization

Michael Cox
MRJ/NASA Ames Research Center
Microcomputer Research Labs, Intel Corporation
<mbc@nas.nasa.gov>

David Ellsworth
MRJ/NASA Ames Research Center
<ellswort@nas.nasa.gov>

[redacted] We call this the problem of *big data*. When data sets do not fit in main memory (*in core*), or when they do not fit even on local disk, the most common solution is to acquire more resources. [redacted]

Abstract

In the area of scientific vis ... often very large. In visualiza ... Dynamics (CFD) in particular, in ... 100 Gbytes, and are expected to scale with the ability of supercomputers to generate them. Some visualization tools already partition large data sets into segments, and load appropriate segments as they are needed. However, this does not remove the problem for two reasons: 1) there are data sets for which even the individual segments are too large for the

problem of *big data*. When data sets do not fit in main memory (*in core*), or when they do not fit even on local disk, the most common solution is to acquire more resources. This *write-a-check* algorithm has two drawbacks. First, if visualization algorithms and tools are worth developing, then they are worth deploying to more production-oriented scientists and engineers who may have on their

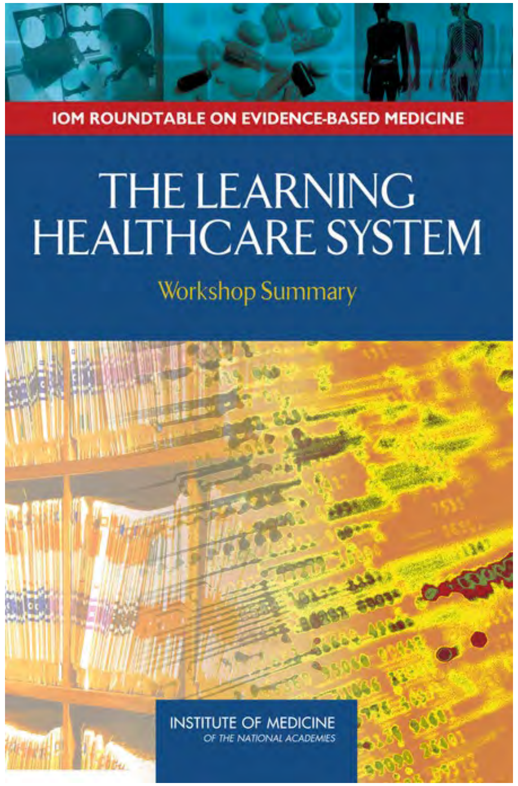
https://www.dictionary.com

Cox, M., & Ellsworth, D. (1997, October). Application-controlled demand paging for out-of-core visualization. In *Proceedings. Visualization'97 (Cat. No. 97CB36155)* (pp. 235-244). IEEE.

Big Data in Healthcare

- EHR stores large amounts of patient data
- Widespread digitalization in healthcare
  - Exponentially increasing amounts of data from many different sources
- Potential rich source for research and data mining
- 80% of health data is unstructured

… **professional judgment will always be vital to shaping care,** *but the amount of information required for any given decision* is moving beyond unassisted **Human Capacity**



Olsen, LeighAnne, Dara Aisner, and J. Michael McGinnis. "The learning healthcare system." (2007).

http://pestianlab.cchmc.org

Epilepsy

- Epilepsy is one of the leading neurological disorders in the United States, affecting more than 479,000 children and over 2 million adults

- 30% of epileptic patients are intractable
  - 55-59% of children are seizure-free after neurosurgery
  - 77% have improved quality of life with appropriate surgery

- Differentiate between intractable and non-intractable

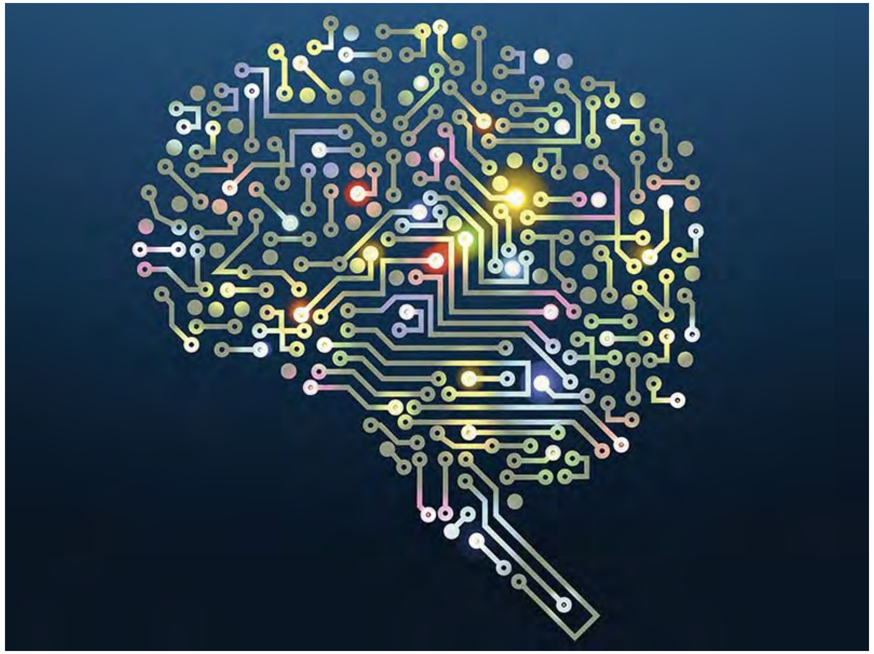
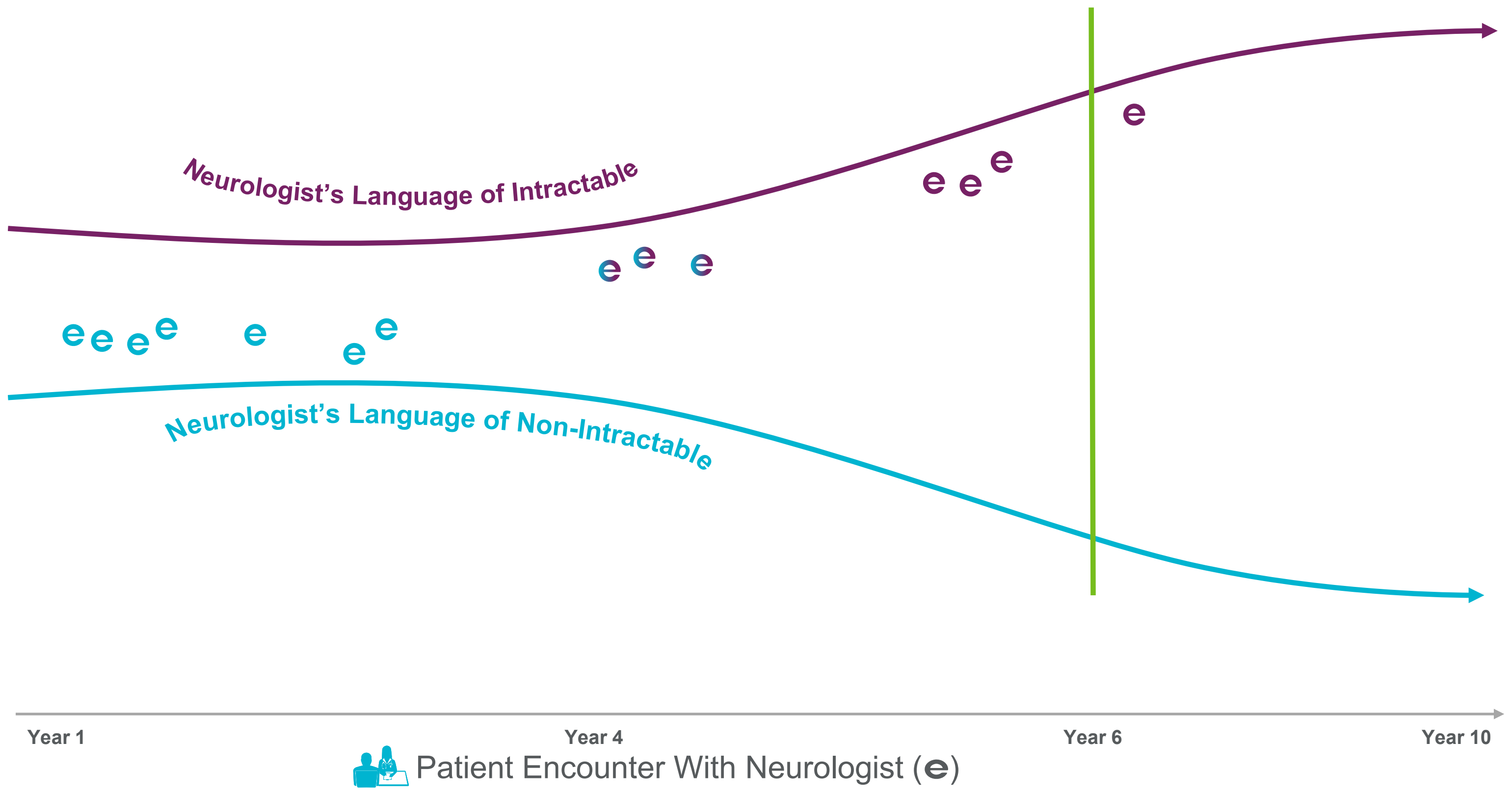


Image Source: https://www.thegreatcourses.com/courses/your-best-brain-the-science-of-brain-improvement.html

Epilepsy Surgery Identification

- Early identification and referral of children who are potential surgery candidates is a laborious and complex process
  - ► Approximately 6 years from the date of diagnosis to surgery with a 10-year national average
- Patient outcomes after surgery are good with approximately a 3% complication rate
- While general rules exist, there is no streamlined process to identify patients meeting criteria for neurosurgical intervention

Epilepsy Neurosurgery Candidate Identification



http://pestianlab.cchmc.org

How Does It Know Patients Are Eligible?

Looked to automatically differentiate between seizure-free and those eligible to be referred for surgical evaluation

<u>Intractable (referred)</u>

- Surgery
- Idiopathic localization
- Increase
- Epilepsy

<u>Seizure-free (not referred)</u>

- Excellent-control
- Bi-laterally
- First

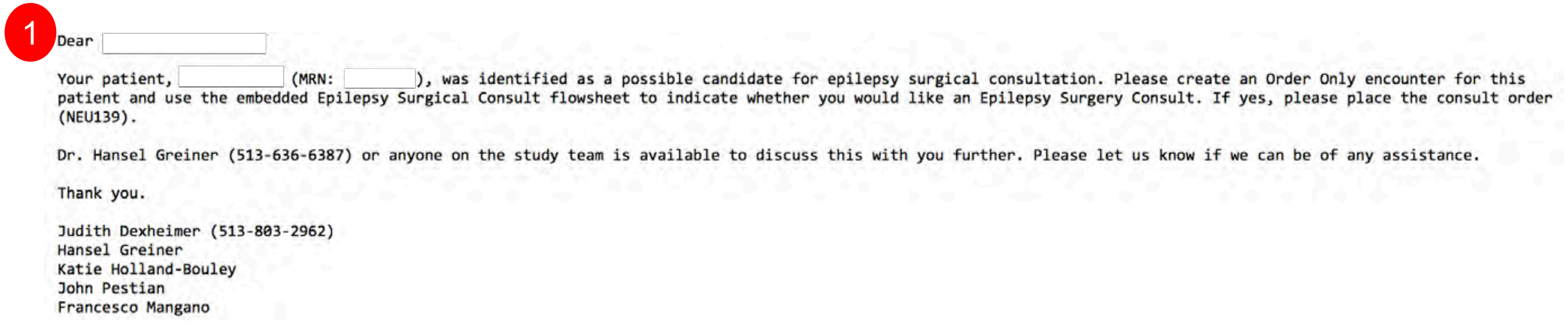
How Do We Put It Into Practice?

- Involve end-users in the intervention design
- Automate processes to run without additional interventions

- Email or In-basket message sent to Neurology providers
- Automatically identifies eligible patients each Sunday

Kawamoto, Kensaku, et al. "Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success." *Bmj* 330.7494 (2005): 765.

Sample Alerts


1

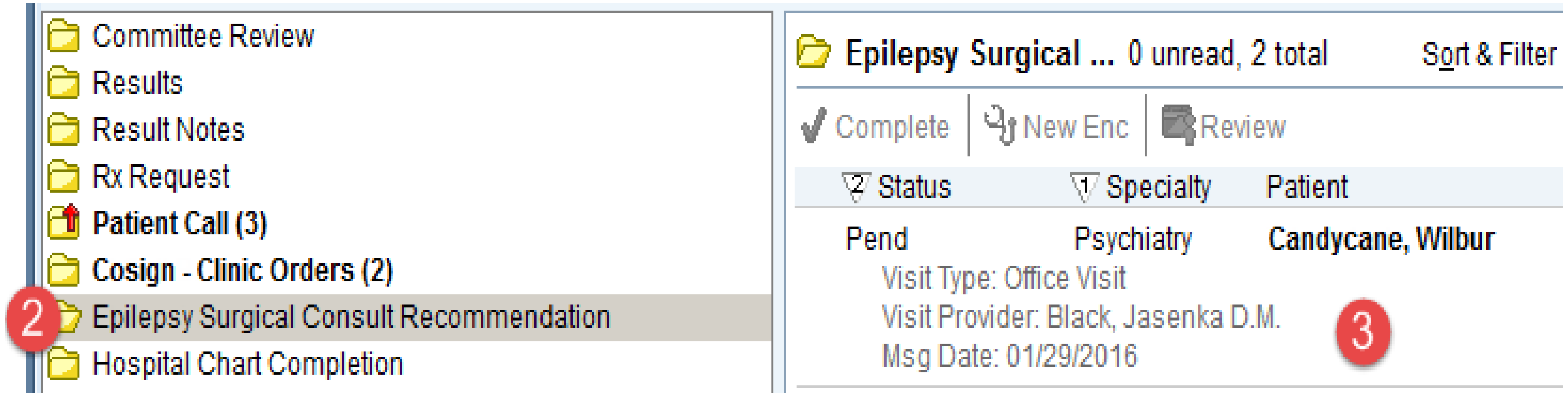
Dear

Your patient, (MRN:), was identified as a possible candidate for epilepsy surgical consultation. Please create an Order Only encounter for this patient and use the embedded Epilepsy Surgical Consult flowsheet to indicate whether you would like an Epilepsy Surgery Consult. If yes, please place the consult order (NEU139).

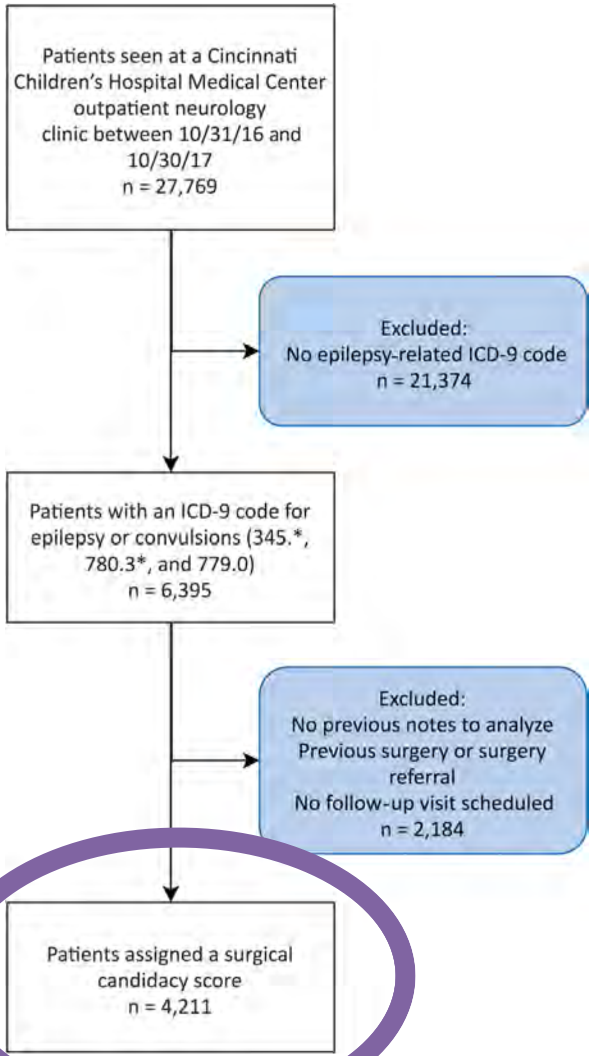
Dr. Hansel Greiner (513-636-6387) or anyone on the study team is available to discuss this with you further. Please let us know if we can be of any assistance.

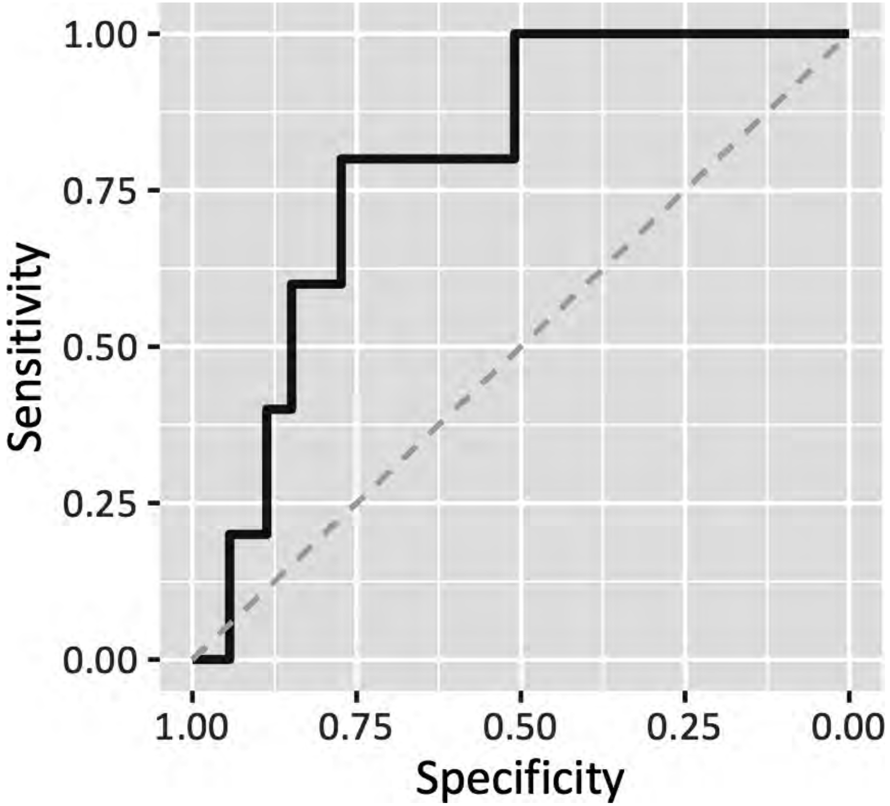
Thank you.

Judith Dexheimer (513-803-2962)
Hansel Greiner
Katie Holland-Bouley
John Pestian
Francesco Mangano



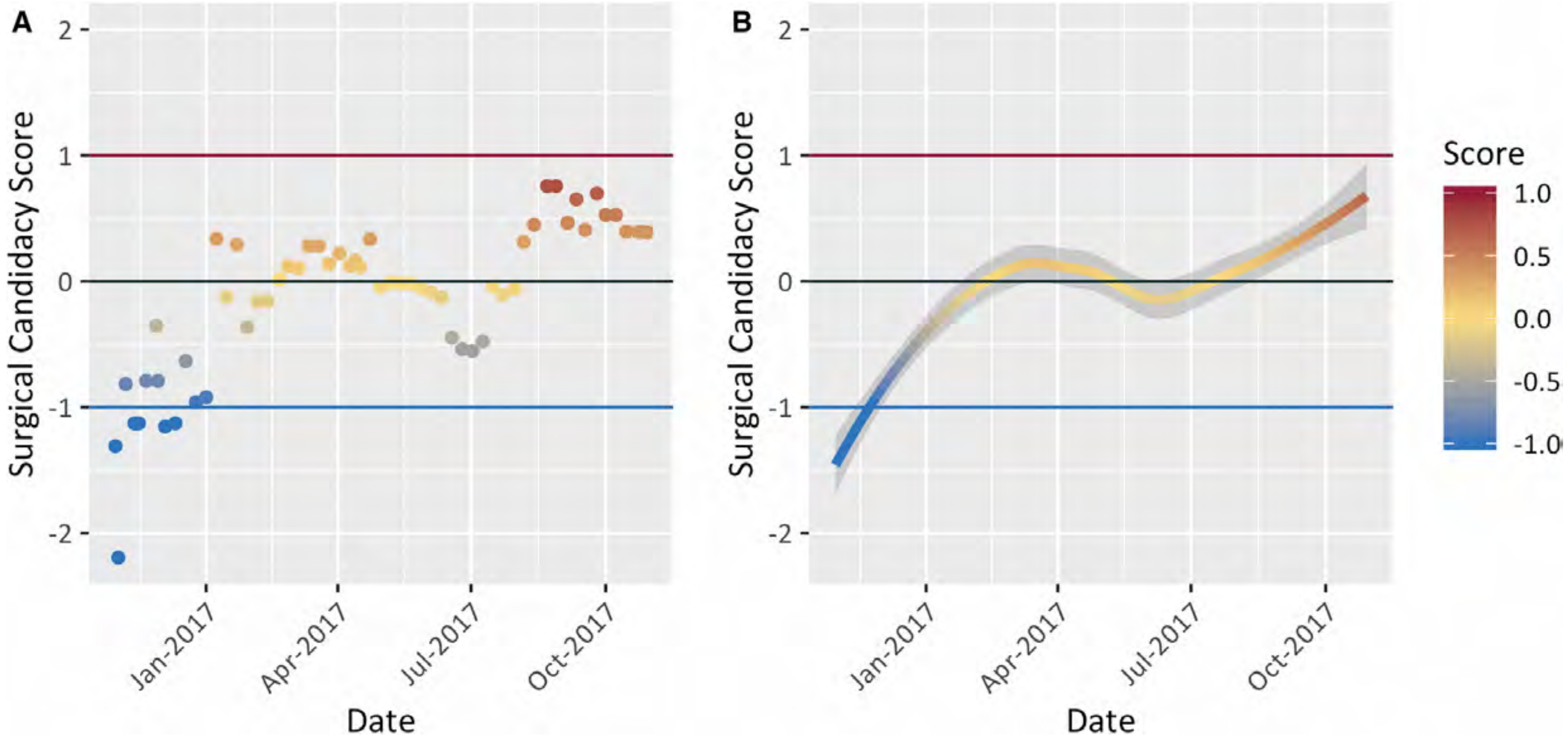
Prospective NLP Evaluation



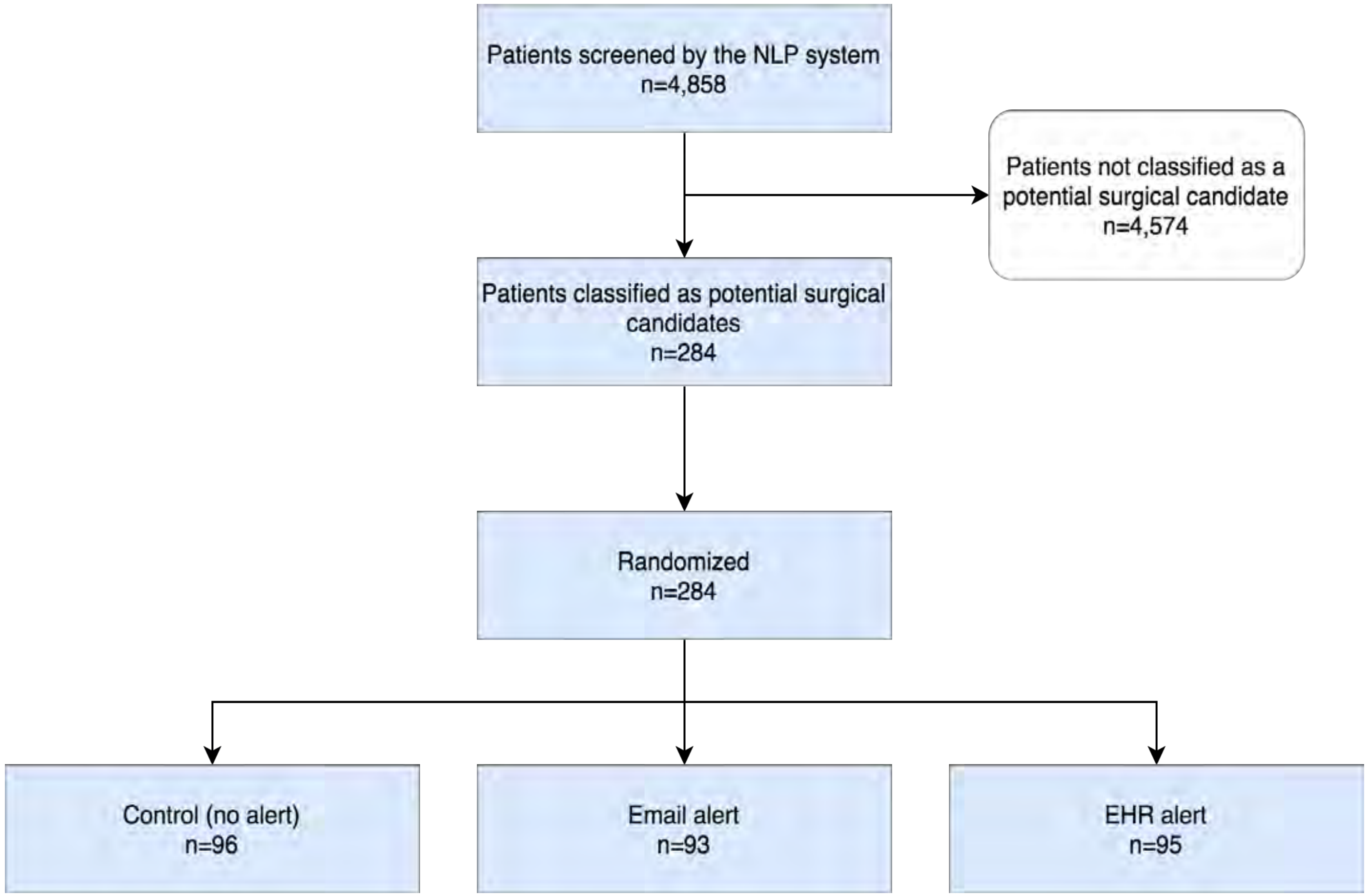


Epilepsia, Volume: 61, Issue: 1, Pages: 39-48, First published: 29 November 2019, DOI: (10.1111/epi.16398)

Prospective NLP Evaluation

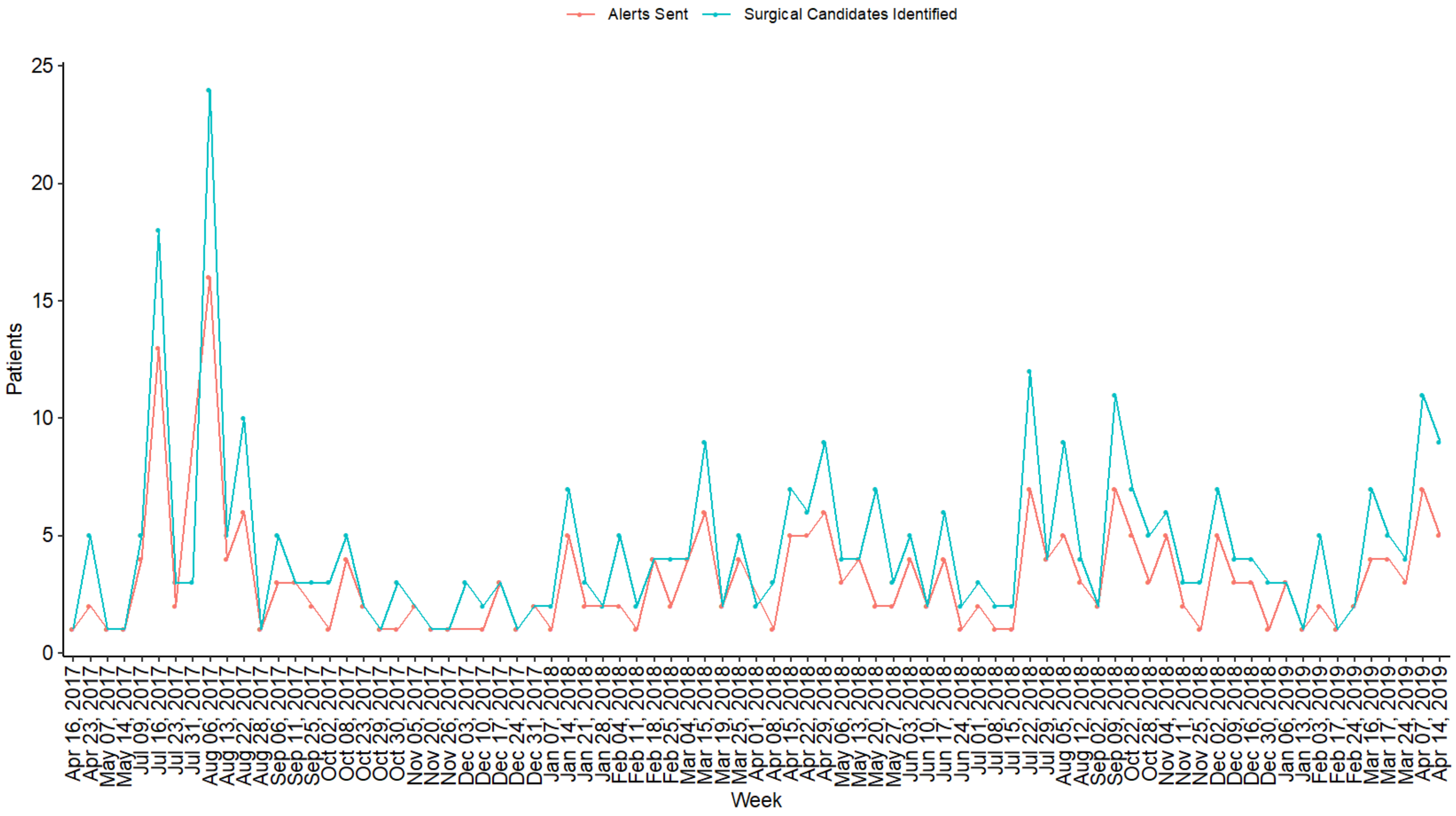


Prospective Provider Evaluation

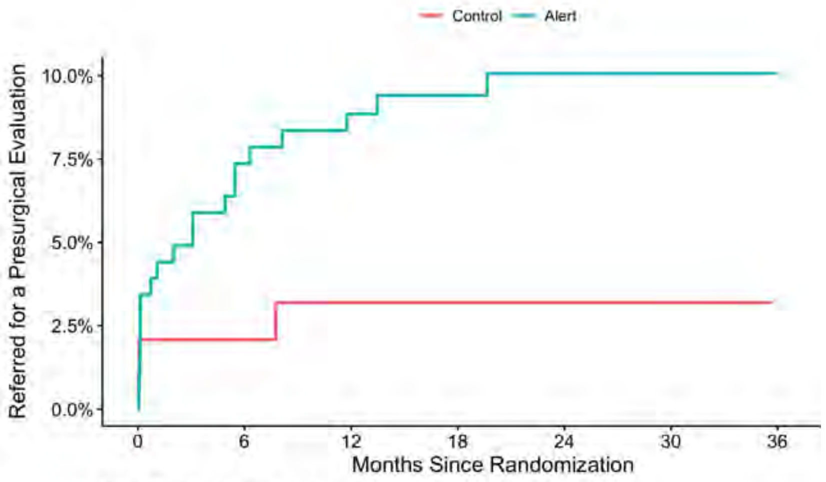


Dexheimer, et al. Unpublished

Prospective Provider Evaluation

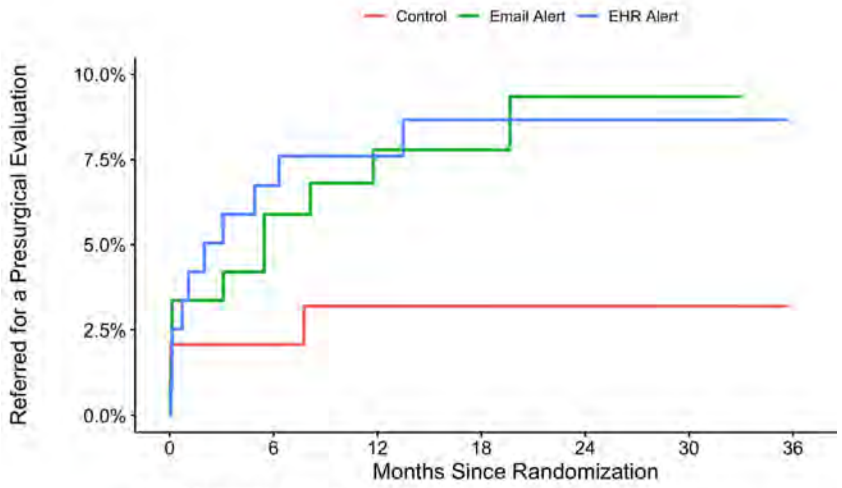


Prospective Provider Evaluation



N = Patients not referred (Patients referred)

	0	6	12	18	24	30	36
Control	96 (0)	92 (2)	78 (3)	58 (3)	35 (3)	15 (3)	0 (3)
Alert	204 (0)	188 (15)	184 (18)	143 (19)	97 (20)	56 (20)	1 (20)

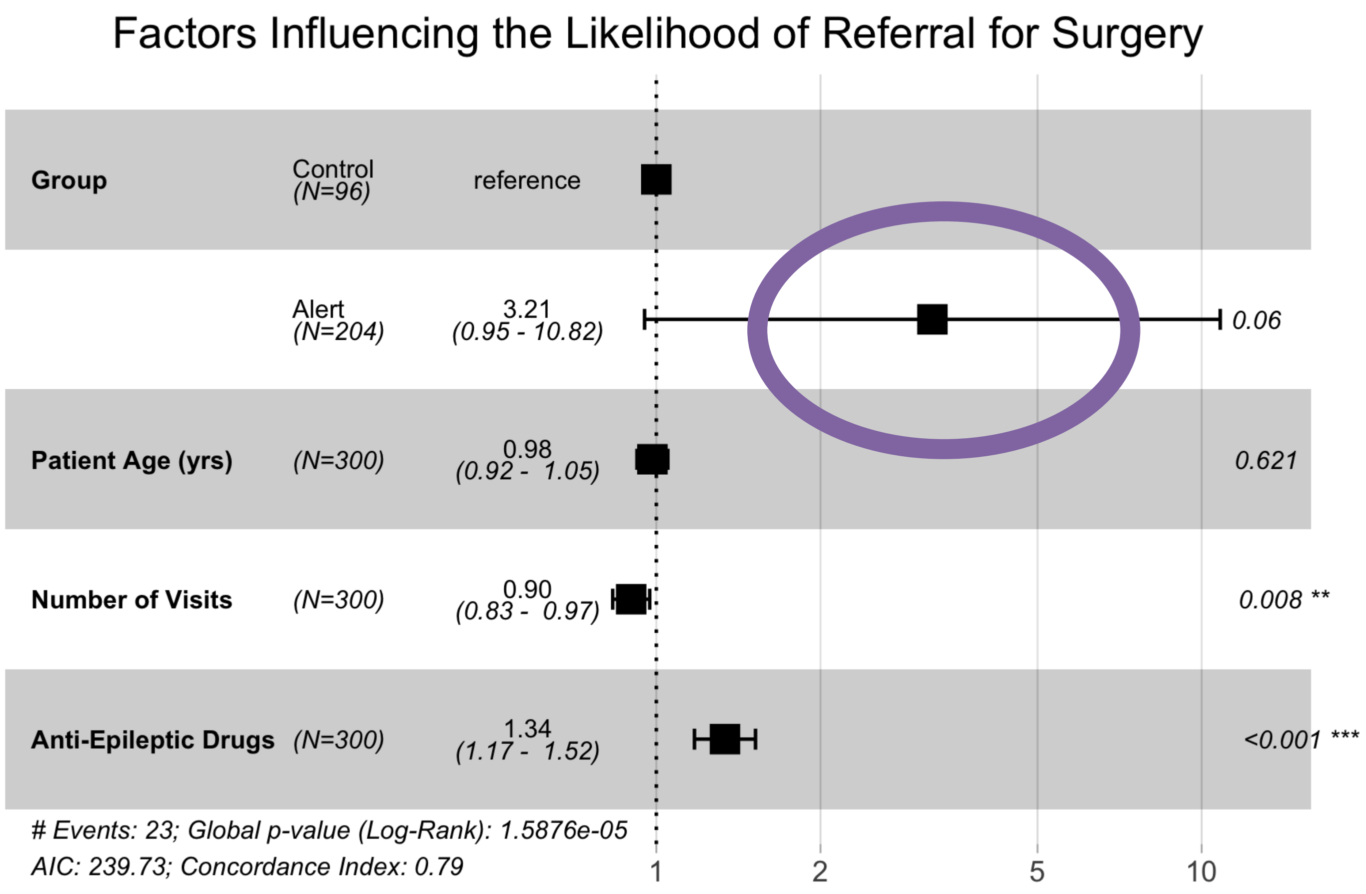


N = Patients not referred (Patients referred)

	0	6	12	18	24	30	36
Control	96 (0)	92 (2)	78 (3)	58 (3)	35 (3)	15 (3)	0 (3)
Email Alert	119 (0)	111 (7)	93 (9)	65 (9)	34 (10)	15 (10)	0 (10)
EHR Alert	119 (0)	109 (8)	97 (9)	67 (10)	42 (10)	22 (10)	0 (10)

Dexheimer, et al. Unpublished

Prospective Provider Evaluation



Dexheimer, et al. Unpublished

Benefits of EHR Integration

- Provider involvement in design
  - ► Identification system (NLP)
  - ► Non-interruptive alerts
- More patients identified compared to no alerts
- Providers were able to decide prior to the visit, not during the visit
- Decisions could be deferred until a future visit to give time for discussion

What Can We Do Next?

- Improve the classifier
  - ▶ Add in additional data sources
- Fully integrate it with clinical care
- Expand to other hospitals

Assessing the similarity of surface linguistic features related to epilepsy across pediatric hospitals

Brian Connolly, Pawel Matykiewicz, K Bretonnel Cohen, Shannon M Standridge, Tracy A Glauser, Dennis J Dlugos, Susan Koh, Eric Tham, John Pestian

Journal of the American Medical Informatics Association, Volume 21, Issue 5, September 2014, Pages 866–870, https://doi.org/10.1136/amiajnl-2013-002601

Published: 01 April 2014 **Article history** ▾

What Does The Future Hold?

- We can improve pediatric care with unbiased machine learning algorithms

- More opportunities for machine learning development and implementation

- Testing across larger datasets and hospitals

Contact Information

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Cincinnati Children's®



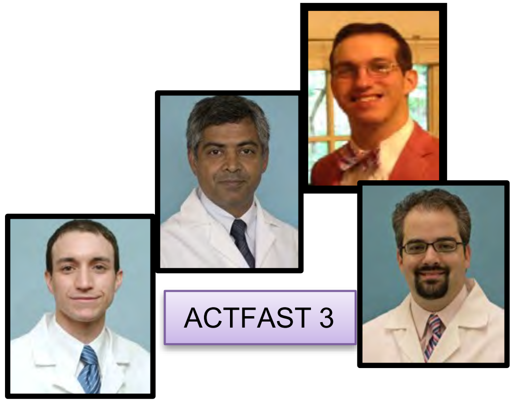
Anesthesiology Control Tower: Feedback Alerts to Supplement Treatment (ACTFAST)

Michael Avidan, MBBCh,FCASA
Dr. Seymour and Rose T. Brown Professor of Anesthesiology
Washington University School of Medicine in St. Louis

Special Thanks

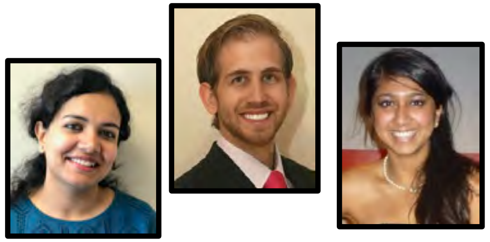
ACTFAST 1

TECTONICS



ACTFAST 3

ACTFAST 2



Special Thanks

Anesthesiologists

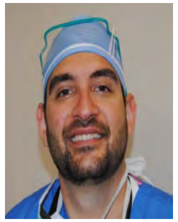
Special Thanks







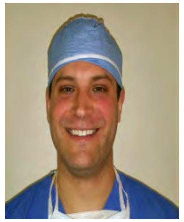


CRNAs






Using AI to Improve Health and Healthcare

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Using Artificial Intelligence to Improve Health and Healthcare

Artificial intelligence (AI), defined as the ability of computers to learn human-like functions or tasks, has shown great promise. What was previously considered the sole domain of human cognition is already being leveraged successfully across many industries, including healthcare. The rapid digitization of health data with health IT in the United States has created unprecedented opportunities in the use of AI in healthcare. The AHRQ Health IT Program is leading research efforts in this area including the following research:

Dr. Michael Avidan and his research team at the Washington University School of Medicine are working to develop and evaluate an air traffic control-like command center for operating rooms. Anesthesiology Control Tower: Feedback Alerts to Supplement Treatment (ACTFAST) will apply data mining and machine learning to forecast adverse patient outcomes using data from the perioperative electronic medical record and real-time physiological data. The Anesthesiology Control Tower (ACT) will track and deliver alerts to anesthesiologists' personal communication devices and enable expert clinicians located outside the operating room to provide attending anesthesiologists with real-time decision support.

ACTFAST

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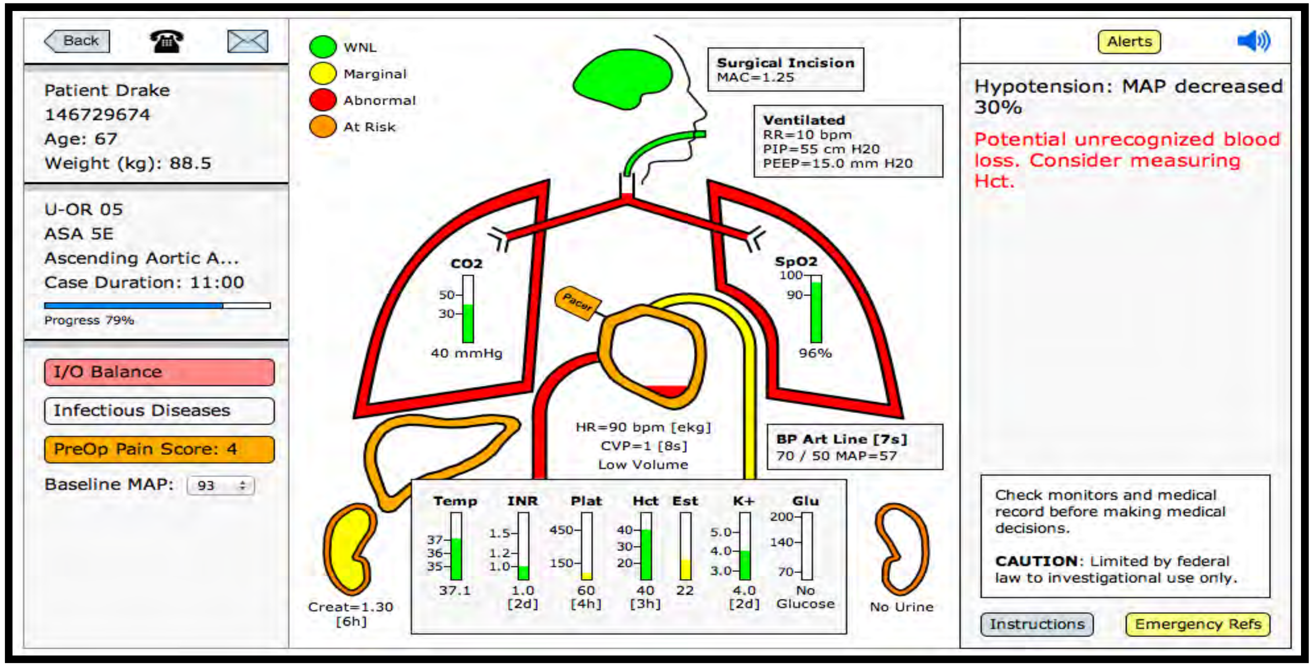
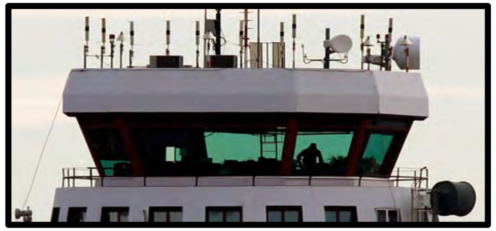
https://digital.ahrq.gov/2018-year-review/research-summary/emerging-innovative-newly-funded-research/using-artificial-intelligence-improve-health-and-healthcare

Anesthesiology Control Tower





Final Report to AHRQ

1. TITLE PAGE

Title: Anesthesiology Control Tower: Feedback Alerts to Supplement Treatment (ACTFAST)

Principal Investigator: Michael Avidan, MBBCh

Key Team Members: Arbi Ben Abdallah, PhD; Yixin Chen, PhD; Brad Fritz, MD; Daniel Helston, MD; Sachin Kheterpal, MD; Teresa Murray, MD; Mary Politi, PhD; Anshuman Sharma, MD

Other Team Members: Thaddeus Budelier, Shreya Gowasni, Alex Kronzer, Sherry McKinnon

Organization: Washington University School of Medicine

Inclusive Dates of Project: 04/01/2017 – 03/31/2020

Federal Project Officer: Janey Hsiao, AHRQ

Acknowledgment of Agency Support: This project was supported by grant number R21HS24581 from the Agency for Healthcare Research and Quality.

Grant Number: R21HS24581

https://digital.ahrq.gov/sites/default/files/docs/citation/r21hs024581-avidan-final-report-2020.pdf

The 3 AIMS of ACTFAST

- ***Aim 1: Develop, refine, and validate forecasting algorithms for adverse outcomes***
- ***Aim 2: Assess the usability of an ACT for the operating suite***
- ***Aim 3: Assess whether the ACT improves clinician compliance with standards of care and surrogate measures of patient outcomes***

https://digital.ahrq.gov/sites/default/files/docs/citation/r21hs024581-avidan-final-report-2020.pdf

Open Access Protocol

BMJ Open

Using machine learning techniques to develop forecasting algorithms for postoperative complications: protocol for a retrospective study

Bradley A Fritz,[1] Yixin Chen,[2] Teresa M Murray-Torres,[1] Stephen Gregory,[1] Arbi Ben Abdallah,[1] Alex Kronzer,[1] Sherry Lynn McKinnon,[1] Thaddeus Budelier,[1] Daniel L Helsten,[1] Troy S Wildes,[1] Anshuman Sharma,[1] Michael Simon Avidan[1]

Fritz BA, et al. BMJ Open 2018;8:e020124

Bradley A. Fritz et al.

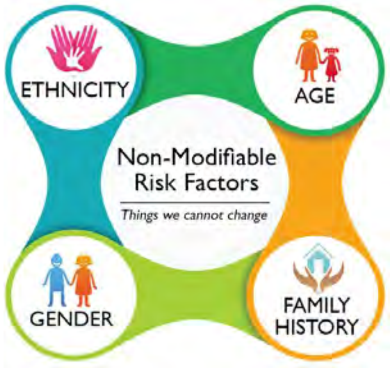
Predicting postoperative mortality with machine learning

Funding

National Science Foundation (1622678); Division of Information and Intelligent Systems; Agency for Healthcare Research and Quality (R21 HS24581-01).

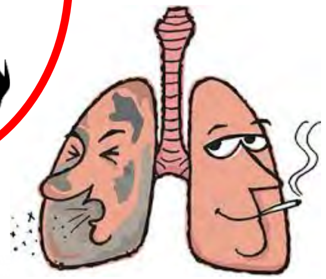
ACTFAST2

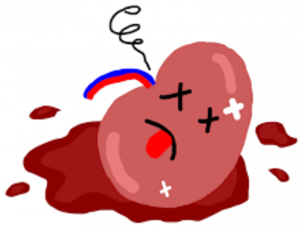
Patient Characteristics



Intraoperative Time-Series Data

FORECASTING ALGORITHMS





Postoperative Outcomes

Our Approach

Dataset with ~95,000 unique patients

- We use **44 preoperative features**, containing both numerical and categorical data types
- For the in-op time series features, we delete sparse time series with many missing values and select **10 most important time series**. We tested with three time series lengths, 30-min, 45-min, and 60-min
- We randomly split the dataset into training set (~60,000 patients), validation set (~17,000 patients), and testing set (~17,000 patients)

Architecture of the Multipath Convolutional Neural Network

Combines several columns into a single vector-valued column

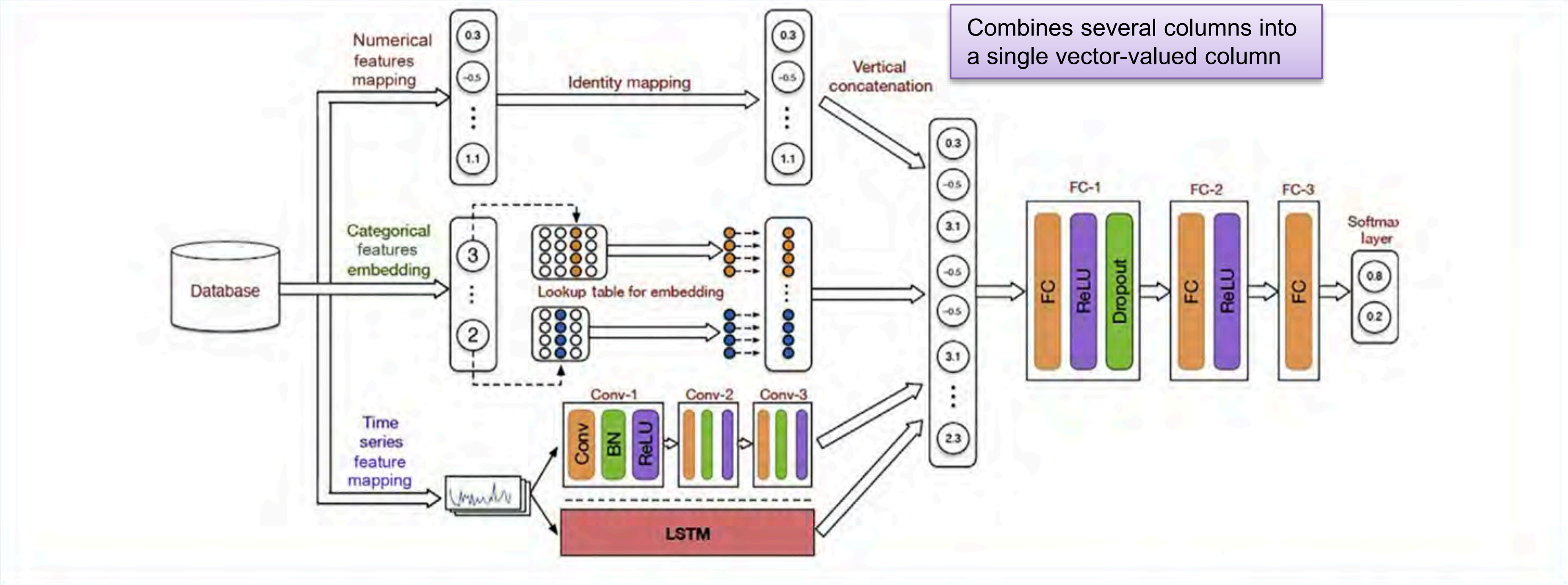


Fig 1. Overall architecture of the multipath convolutional neural network. BN, batch normalisation; Conv, convolution; FC, fully connected block; LSTM, long short-term memory; ReLU, rectified linear unit.

Multi-path convolutional deep neural network (MPCNN) that can directly handle a heterogeneous dataset

British Journal of Anaesthesia, 123 (5): 688-695 (2019)

Predicting Postoperative Death

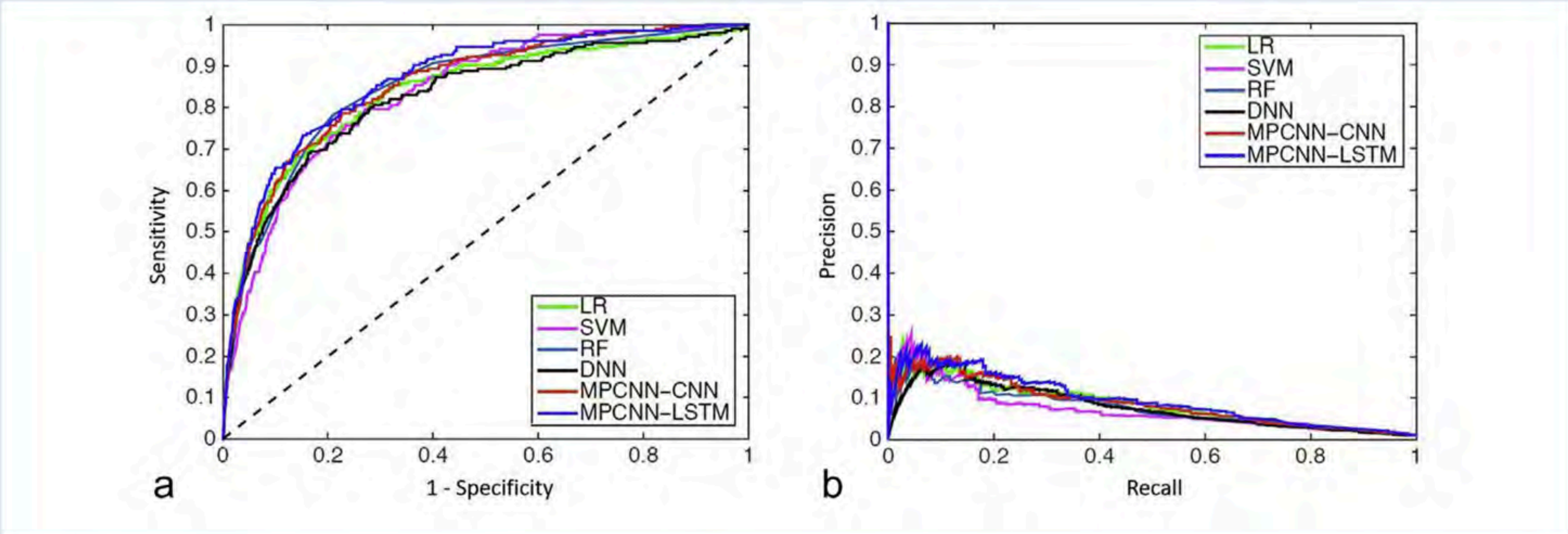


Fig 2. Performance characteristic curves for the multipath convolutional neural network using convolution neural network (MPCNN–CNN), multipath convolutional neural network using long short-term memory (MPCNN–LSTM), deep neural network (DNN), random forest (RF), support vector machine (SVM), and logistic regression (LR). (a) The receiver operating characteristic curves for each model. (b) The precision–recall curves for each model.

MPCNN-LSTM: AUC = 0.87 with a specificity of 0.95 and a sensitivity of 0.50, and a precision (PPV) ~10%.

British Journal of Anaesthesia, 123 (5): 688-695 (2019)

Not the End of the Story

It turns out that it is really important that you input accurate data when you develop your models.

Update to 'Deep-learning model for predicting 30-day postoperative mortality' (*Br J Anaesth* 2019; 123: 688–95)

Bradley A. Fritz*, Mohamed Abdelhack, Christopher R. King, Yixin Chen and Michael S. Avidan

Publication Date: 7 May 2020

The Mystery of the Missing Deaths

- While performing additional work with the retrospective dataset we had used to train and test the described model, we discovered that many deceased patients had not had their records updated to reflect their death

- In the updated dataset, 2296 of 96 968 patients (2.4%) died within 30 days after surgery, including 1355 previously unlabeled deaths

A Marked Improvement

Table 1 Performance of multipath convolutional neural network model (MPCNN) compared with deep neural network (DNN) without time series, random forest (RF), support vector machine (SVM), and logistic regression (LR). Both the long short-term memory (LSTM) and convolution neural network (CNN) methods of handling time-series data are presented. AUROC, area under receiver operating characteristic curve; AUPRC, area under precision-recall curve; CI, confidence interval

Model	Published results		Updated results	
	AUROC (95% CI)	AUPRC (95% CI)	AUROC (95% CI)	AUPRC (95% CI)
MPCNN-LSTM	0.867 (0.835–0.899)	0.095 (0.085–0.109)	0.910 (0.897–0.924)	0.325 (0.280–0.372)
MPCNN-CNN	0.855 (0.822–0.887)	0.089 (0.077–0.100)	0.907 (0.894–0.920)	0.294 (0.251–0.339)
DNN	0.825 (0.790–0.856)	0.078 (0.068–0.088)	0.917 (0.905–0.930)	0.342 (0.296–0.389)
RF	0.848 (0.815–0.882)	0.078 (0.067–0.088)	0.923 (0.911–0.935)	0.409 (0.360–0.460)
SVM	0.836 (0.802–0.870)	0.072 (0.062–0.081)	0.913 (0.900–0.926)	0.314 (0.271–0.359)
LR	0.837 (0.803–0.871)	0.085 (0.074–0.096)	0.916 (0.904–0.929)	0.323 (0.279–0.368)

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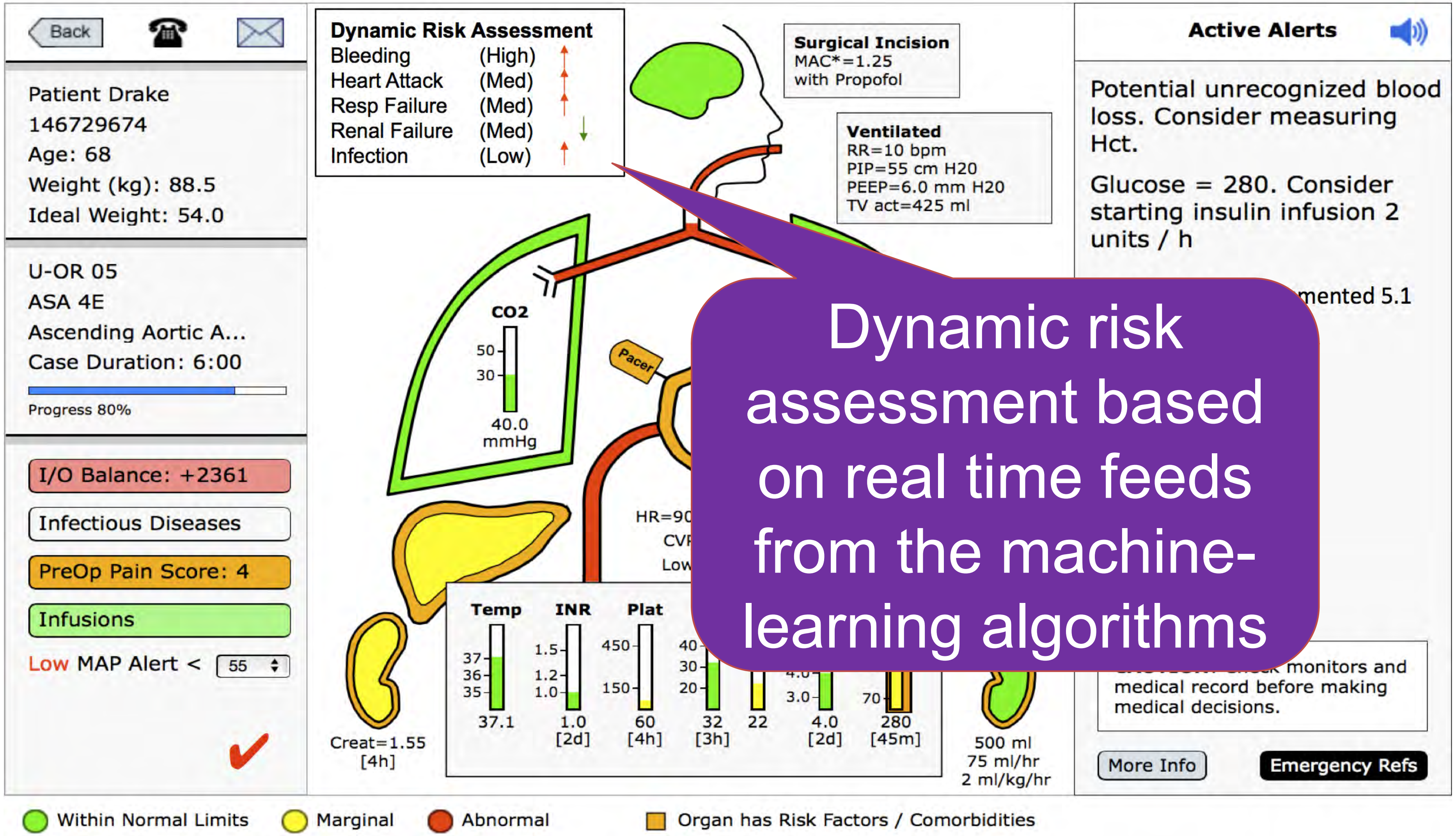
A Word of Caution

Vigilance regarding data quality is a key step in machine learning, and this process does not stop once a model has been trained. <u>Models intended for use in the clinical space must be continuously re-evaluated and updated</u>.

In our case, reusing a dataset for multiple analyses exposed a systematic error in outcome labels. A key takeaway from our experience is that <u>incomplete labelling of the target variable can impair the performance of prediction models, even when robust analytic methods are applied</u>.


Mortality ROC curve
True Positive Rate (sensitivity)
False Positive Rate (1-specificity)
Machine-Learning Predictive Algorithms
Waveforms from the ORs and PACUs
Live Video Feed from OR
AlertWatch Dashboard
Epic Dashboard
AlertWatch Patient View
Anesthesiology Control Tower Team



Dynamic risk assessment based on real time feeds from the machine-learning algorithms

Any Questions?

Contact Information

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School of Medicine

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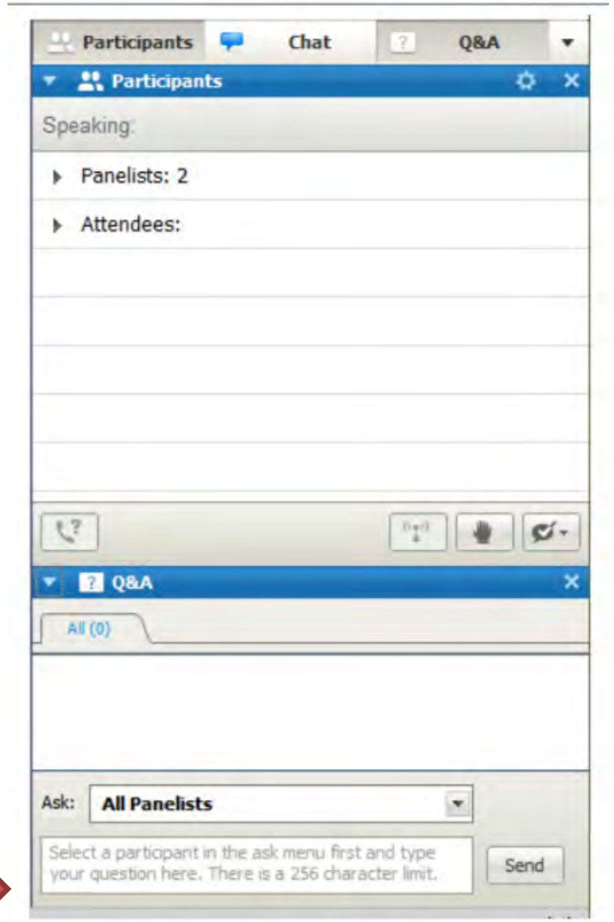

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